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Measuring energy poverty: Focusing on what matters

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ABSTRACT

The provision of modern energy services is recognised as a critical foundation for sustainable development, and is central to the everyday lives of people. Effective policies to dramatically expand modern energy access need to be grounded in a robust information-base. Metrics that can be used for comparative purposes and to track progress towards targets therefore represent an essential support tool. This paper reviews the relevant literature, and discusses the adequacy and applicability of existing instruments to measure energy poverty. Drawing on those insights, it proposes a new composite index to measure energy poverty. Both the associated methodology and initial results for several African countries are discussed. Whereas most existing indicators and composite indices focus on assessing the access to energy, or the degree of development related to energy, our new index – the Multidimensional Energy Poverty Index (MEPI) – focuses on the deprivation of access to modern energy services. It captures both the incidence and intensity of energy poverty, and provides a new tool to support policy-making.

Contents

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1. Introduction

Energy is central to addressing many of today's global development challenges, including poverty, inequality, climate change, food security, health and education. The link between energy and the Millennium Development Goals (MDGs) has been discussed extensively in the literature (see, e.g. [1,2]) and energy poverty is undermining their achievement.

Current actions to eradicate energy poverty are falling short both in terms of scale and pace [36]. In fact, if current trends continue, more people will be without modern energy access in 2030 than currently [3]. Changing this pathway requires global political commitment that goes beyond abstraction and sets out actions and associated benchmarks [35]. A goal of providing universal access to modern energy services has recently been put forth to the international community [4]. The current lack of quality data will hamper this effort.

The development of tools to support the monitoring and reporting of progress towards widespread energy access is thus instrumental. This paper reviews a series of specific metrics and analyses the methodological strengths and shortcomings of various models. We address an analytical gap by laying the foundation for a novel composite index to measure energy poverty as a complement to existing tools. We also provide initial results to demonstrate its applicability.

2. The use of indicators and composite indices

The use of indicators is widespread. Indicators are useful as proxies to quantify and analyse performance, and therefore provide valuable insights for policy analysis and design, as well as for wider communication. IAEA [5, p. 2] reflected that, '. . .indicators are not merely data; rather, they extend beyond basic statistics to provide a deeper understanding of the main issues and to highlight important relations that are not evident using basic statistics. They are essential tools for communicating energy issues related to sustainable development to policymakers and to the public, and for promoting institutional dialogue.'

Bazilian et al. [35] review a selection of metrics in the sustainable development and energy space. Three broad categories can be identified to classify the type of metrics: single indicators; set of individual, non-aggregated indicators (or 'dashboard'); and composite indices (see Table 1).

2.1. Precedents specific to energy poverty

This section provides a brief review of the existing literature on metrics that can be used to quantitatively assess energy poverty.

The Energy Indicators for Sustainable Development (EISD) provides definitions, guidelines and methodologies for the development and use of a set of energy indicators [5,6]. More specific to energy poverty, Foster et al. [7] use three individual measures to quantify it, based on a pre-defined fuel poverty line. More recently, Mirza and Szirmai [8] developed a new composite index to measure the degree of energy poverty amongst rural households in rural Pakistan. The Energy Development Index (EDI) is a composite measure of energy use in developing countries [9]. The report 'Poor people's energy outlook 2010' [10] suggests an energy access index based on six essential energy services for which a minimum level of service is prescribed. In parallel, it introduces a hybrid set of indicators that assign a numerical value to qualitative aspects of energy access in three main supply dimensions, namely household fuels, electricity and mechanical power.

2.2. Methodological insights

Precedents, both within and outside of the energy sector, have produced a rich set of lessons from which to draw on when considering developing a new metric to measure and report on energy poverty. A mix of statistical rigour, transparency, data availability, political attractiveness, simplicity, and usefulness for policy design is wishful. The section below discusses the strengths and weaknesses of various methodological aspects.

2.2.1. Uni- vs. multi-dimensionality

Single indicators are straightforward to handle. They provide a powerful, unbiased message that is easy to interpret with regard to one specific dimension. On the other hand, such metrics present a narrow picture of the issue measured. While perhaps appropriate in some cases (e.g. measuring the level of economic activity with gross domestic product), single indicators are often unsuitable for less tangible issues, such as sustainable development or poverty.

Complex issues such as human development are multidimensional in their very nature. Their assessment therefore requires a framework in which various elements can be captured. A number of initiatives aim to provide a set of individual indicators. Such 'dashboards' depict a much more comprehensive representation of the issue at hand. For instance, the Millennium Development Goals Indicators programme helps track progress on the commitment made in the United Nations Millennium Declaration with a battery of over 60 indicators.

Nonetheless, evaluating changes in a large number of indicators and deriving meaningful insight is no easy task. Indeed, tracking trends over time, or carrying out cross-country comparison, based on a 'dashboard' of indicators might prove impracticable. Beside this, it is useful in some cases to quantify multiple attainments, such as the incidence of multiple deprivations. In such instances, there is no way to avoid resorting to some form of aggregation model.

As a compromise between the simplicity of uni-dimensional indicators and the need to account for the multidimensional nature of some issues, composite indices were created. They represent an attempt to overcome the shortcomings of one-dimensional indicators while at the same time produce an outcome that condenses the information to single, easy to interpret metrics.

2.2.2. Composite indices

Composite indices are single numerals calculated from a number of variables that represent the aggregated value of a dimension that in itself might be elusive (e.g. sustainable development) on the basis of an underlying model. Based on a set of sub-indicators that might or might not have a common unit of measurement, they aim to capture the multidimensional aspects of an issue that cannot be depicted in a single indicator. The lack of common unit does not imply incomparability. Multi-criteria theory provides tools to overcome issues related to incommensurability [11].

Table 1
Broad categories of sustainable development and energy metrics with examples.

Category	Example	Initiator	Reference
Single indicators	International poverty line ($1 a day)	The World Bank	Chen and Ravallion [39]
Set of individual indicators, or 'dashboard'	Millennium Development Goals Indicators Energy Indicators for Sustainable Development	UN IAEA	UNSD, DESA, UN [42] IAEA [5], Vera and Langlois [6]
Composite indices	Human Development Index Energy for Development Index	UNDP IEA	UNDP [22] IEA [9]

Composite indices have been widely used as an alternative to single, uni-dimensional values. The rationale for developing composite indices lies in the need for aggregating information to a level that makes analysis convenient. They have proven to be useful for benchmarking performance, for example between countries. A large number of institutions are producing composite indices in a wide variety of research problems and fields [12]. A list of examples is available in Saisana and Tarantola [13].

The drawback of composite indices is that, by combining variables, the process includes some form of reduction to a single measure, with all the associated methodological issues and required assumptions and simplifications it implies (including value judgments). Composite indices can be misleading in terms of policy, particularly in the case whereby the analysis of the results is too simplistic and/or when the indicator is poorly constructed. In that regard, Ravallion [14] underlines the common gap between the theoretical ideal and practical measurement.

Various publications have underlined the lack of theoretical underpinning of a number of composite indices (e.g. [13,15,16]), highlighting issues related to the aggregation model and/or the weightings in particular. The Human Development Index (HDI), arguably the most influential metric of human development, and other similar composite indices have been widely criticised in the development literature for inconsistencies, methodological flaws and redundancy [17–21]. As a result of these critiques, the methodology to compile the HDI has changed a number of times over the years. Symptomatic of various views amongst experts in the field is also the recent heated discussion between the 'aggregators' and 'non-aggregators' [38] triggered by the launch of the Multidimensional Poverty Index (MPI) in the 2010 Human Development Report (see [22]).

Different aggregating methods are available for the design of a composite index (for review and description, see, e.g. [23]). Commonly used is the simple additive method, or weighted sum. This model has been widely applied for its transparency and ease of use, including by non-experts. An alternative to the weighted sum is the weighted geometric mean aggregation. Ebert and Welsch [24] see advantages in using such a model but also note its limitations. Other, more advanced approaches deriving from multi-criteria decision analysis are commonly more complicated to compute and the interpretation of the results is less intuitive.

2.2.3. The issue of weight and compensability

The issue of weight is somewhat controversial. One can argue that all criteria considered in an index need not necessarily have the same relative importance or symmetrical importance (in the jargon of decision theory literature). However, theoretically sound frameworks to derive rational weighting approaches are difficult to construct [16]. Assigning weights can be challenging and is an arbitrary and value-driven process. Some have suggested participatory methods for this purpose. However, consensus over the relative importance of various dimensions is challenging, particularly in the case of conflicting objectives. Having noted this, the process of including or excluding criteria, even without weight, is a value judgment per se on the relative importance of the variables.

In the case of compensatory frameworks, such as additive models, critics argue that using weights to embody intensity of importance represents a theoretical inconsistency [25]. Indeed, in the case of linear compensatory aggregation models, weights depend on the measurement scale of the criteria and are to be interpreted as trade-offs, or judgements about compensability, and not as importance factors [15]. In line with this thinking, the aggregation procedure needs to be non-compensatory where weights are used with the meaning of importance coefficients.

2.3. Synthesis

The use of indicators and indices is widespread. However, some concepts, such as sustainable development, are relatively intangible in nature and therefore more challenging to characterize and quantify. Composite indices have been developed as an attempt to capture multidimensionality and/or multiple attainments. Yet, the methodological soundness of some of those indices has been questioned on a number of grounds. This notwithstanding, one can argue that composite indices provide a useful statistical summary of particular issues, bearing in mind their limitations.

There are clear trade-offs in the choice of the aggregation model, notably in terms of loss of information, level of compensability allowed between variables, and ease of use and transparency. Ultimately, the selection of the appropriate method depends primarily on the objective of the index and the target audience.

A hybrid approach would consist of an aggregated set of indicators that are monitored and reported upon individually alongside a composite index which captures the essence of the concept being evaluated. It can reconcile the advantages of a single, easy-to-understand and -interpret composite metric, acknowledging its crude and imperfect nature, with the benefits of providing more detailed information. A wealth of literature [12,13,16,26], from which we draw, provides useful insights for the development of metrics in general and composite indices in particular.

3. The Multidimensional Energy Poverty Index (MEPI): a new metric to measure and report on energy poverty

The provision of detailed and accurate information on energy poverty has the potential to positively influence the design of policy, regulatory and financial strategies to address the issue. We describe a new metric to measure and report on energy poverty to fill an analytical gap. As a starting point, we underline the multidimensional nature of energy poverty, and the need to capture a range of various elements to adequately reflect the complexity of the nexus between access to modern energy services and human development. A multi-criteria framework therefore appears ideally suited. Also, we suggest a composite index as a means of capturing multiple deprivations. Noting the issues related to the use of composite indices, we also report on selected individual indicators.

In contrast to other tools, we focus on quantifying energy deprivation, as opposed to energy access. A number of indices include consumption-based indicators under the assumption that energy

consumption is correlated to development. While recognising the value of such conglomerative approaches, a deprivational perspective offers a valuable complement by focusing specifically on the poor [27], thereby providing a more direct indication of the relevant aspects of poverty.

In addition, we note that relatively limited attention that has been devoted to capturing aspects related to the quality of the energy services delivered and/or their reliability, as well as to the notion of affordability. More importantly, an ideal energy poverty metric should shed light on the issue through the lens of the energy services, which is ultimately what is of importance to people and makes a difference in their lives. Also, most metrics are primarily focused on the supply side or input-oriented data; a better tracking of demand-side elements is desirable. Finally, the algorithm of the metric should ideally be able to accommodate variables of various kinds, like cardinal and ordinal (categorical). Indeed, in the case of an energy poverty metric, some variables are likely to be qualitative, such as the type of fuel used.

3.1. Energy poverty: delimiting the scope

There are a number of attempts to quantitatively define energy poverty (e.g. [7,9,10,28]). Such estimations, however, rest on a set of arbitrary assumptions with regard to the consuming energy devices as well as a normative definition of what a set of basic needs consist of [29]. Also, the quantification of basic needs is contingent to the context (cultural practices, climatic conditions, etc.). Beside levels of energy consumed, various analysts have underlined the importance of the type of energy sources accessible [29] as well as the quality of the supply [10].

For the purpose of this study, we limit the scope to household needs exclusively, while acknowledging that other energy needs exist for a society to develop and thrive. Common energy services demanded in households include: cooking, space heating/cooling, lighting, entertainment/education (radio, TV, computer), services provided by means of household appliances (e.g. refrigerator, washing machine, and electric geyser), telecommunications, and mechanical power.

3.2. Data availability

Any energy poverty metric is likely to be constrained by data paucity. It is therefore necessary to map and review the data that could serve to underpin a measure of energy poverty.

As an example of possible sources, the International Energy Agency (IEA) has been compiling data on energy access at national level since 2004. While some datasets are available in the public domain, others are only accessible through subscription or not at all (e.g. time series). Another source is the MEASURE DHS (Demographic and Health Surveys) project, funded by the United States Agency for International Development (USAID). It is collecting and disseminating nationally representative data on a range of issues such as fertility, family planning, maternal and child health, gender, HIV/AIDS, malaria, and nutrition. Based on household surveys, the information gathered includes a number of indicators related to energy poverty. UNICEF Childinfo reports on similar indicators. Datasets from both sources are available in raw format (output of surveys), as well as in treated form (at national level) for selected indicators.

The great advantage of data based on surveys, from the perspective of energy poverty, is that it provides, beside information on energy related issues, a context. This allows, for instance, decomposition and detailed analysis at sub-national level, by urban vs. rural populations, by level of income/spending, etc., which provides valuable insights of high relevance with regard to the development of customised measures and policies.

Focusing on the deprivation of the services energy provides brings about new challenges with regard to identifying indicators and the availability of data. Quantifying the deprivation in some energy services, such as mechanical power or lighting, might benefit from the use of proxy indicators. Indeed, no comprehensive set of data exists on adequate lighting in households for instance. The choice of the proxy entails some normative judgment, and it is crucial to ensure that it is closely correlated with the service to be quantified. Yet, the use of proxies represents a potentially powerful way to explore new grounds in terms of quantifying energy poverty.

3.3. Identifying and developing a set of relevant variables

The multidimensional nature of energy poverty should be reflected in the choice and structure of the variables. The variables should be carefully selected on the basis of their relevance to the issue at hand and measurability (including availability of sufficient and reliable data). We based our analysis on data from the Demographic and Health Surveys (DHS) [41] as they provide the most comprehensive datasets for the purpose of this analysis. We define the different dimensions of the new energy metric around commonly demanded household energy services to capture various elements as discussed below.

Cooking is amongst the very basic needs. Energy, in the form of heat, is required to prepare meals. We capture elements of energy poverty related to cooking by including the type of fuel used, keeping the notion of convenience in mind. That is, evidence shows that a significant time is spent, mainly by women and children, for daily chores, including collecting fuel for cooking. The use of so-called traditional fuels (firewood, charcoal, dung, etc.) has an important opportunity cost compared to more 'modern' fuels. Also, indoor pollution from incomplete combustion represents a major health issue. We therefore include the type of stove used (with or without hood/chimney) as an imperfect proxy to capture those aspects.

Taking into consideration the limitations on data availability, we do not consider space heating/cooling in the algorithm developed. We suspect nevertheless a correlation between the desirable indicators related to space heating and those related to cooking. Indeed, the type of fuel and device are bound to be related for both energy services.

Electricity access, for the services it provides, is crucial to development. Notably, modern lighting provides numerous developmental benefits. Further, other services such as entertainment, education, and communication for instance are contingent on electricity access. We include indicators related to appliances to capture elements related to the end-use side which are commonly left out of energy access metrics. Incorporating variables related to the ownership of appliances also brings in the notion of affordability. Indeed, the access to electricity, or modern fuels, is of limited use if the potential user does not have the financial means to pay for the fuel or to invest in the appliance to deliver the desired service. We therefore include variables related to the possession of radio or TV and refrigerator. We also include an indicator for telecommunication. Recent history has shown the crucial role of the use of phones and mobile phones in particular, which require the availability of energy, for socio-economic development.

Finally, we recognise the importance of mechanical power (see, e.g. [37]) but do not include it in the analysis because of the lack of reliable data.

We assign relative weights to the various dimensions and indicators, recognising the arbitrary nature of such a process. However, there are strong reasons to believe that the energy poverty variables considered in this energy poverty metric are not of equal importance. This notwithstanding, we stress the fact that a weighting structure is value-laden and that the weights used in this

Table 2
Dimensions and respective variables with cut-offs, including relative weights (in parenthesis).

Dimension	Indicator (weight)	Variable	Deprivation cut-off (poor if. . .)
Cooking	Modern cooking fuel (0.2)	Type of cooking fuel	Use any fuel beside electricity, LPG, kerosene, natural gas, or biogas
	Indoor pollution (0.2)	Food cooked on stove or open fire (no hood/chimney) if using any fuel beside electricity, LPG, natural gas, or biogas	True
Lighting	Electricity access (0.2)	Has access to electricity	False
Services provided by means of household appliances	Household appliance ownership (0.13)	Has a fridge	False
Entertainment/education	Entertainment/education appliance ownership (0.13)	Has a radio OR television	False
Communication	Telecommunication means (0.13)	Has a phone land line OR a mobile phone	False

analysis, as well as the selection of the indicators, are indicative and for the purpose of demonstrating the methodology. Those ought to be adapted to the specificities of the analyses.

3.4. Methodology

The methodology we utilise is derived from the literature on multidimensional poverty measures, notably from the Oxford Poverty and Human Development Initiative (OPHI) [30,32,33], which is inspired by Amartya Sen's contribution to the discussion of deprivations and capabilities. Sen [34] argues for the need to focus on human poverty by considering the absence of opportunities and choices for living a basic human life. The OPHI methodology is further developed to take into account some elements of uncertainty.

Essentially, the MEPI captures the set of energy deprivations that may affect a person. It is composed of five dimensions representing basic energy services with six indicators (see Table 2). A person is identified as energy poor if the combination of the deprivations faced exceeds a pre-defined threshold. The MEPI is the product of a headcount ratio (share of people identified as energy poor) and the average intensity of deprivation of the energy poor.

Formally, the MEPI measures energy poverty in d variables across a population of n individuals. $Y=[y_{ij}]$ represents the $n \times d$ matrix of achievements for i persons across j variables. $y_{ij} > 0$ therefore denotes the individual i achievement in the variable j. Thus, each row vector $y_i=(y_{i1}, y_{i2}, \ldots, y_{id})$ represents the individual i achievements in the different variables, and each column vector $y_j=(y_{1j}, y_{2j}, \ldots, y_{nj})$ gives the distribution of achievements in the variable j across individuals.

The methodology allows weighting the indicators unevenly if desired. A weighting vector w is composed of the elements w_j corresponding to the weight that is applied to the variable j. We define $\sum_{j=1}^{d} w_j = 1$. For the sensitivity analysis, and by means of capturing some of the uncertainty associated with assigning weights, we have applied probabilistic functions to the respective weights. We define the functions by using the deterministic weights shown in Table 2 as the mean of the respective normal probabilistic functions and set the standard deviation to 0.02.

We define z_j as the deprivation cut-off in variable j, and then identify all individuals deprived in any variables. Let $g=[g_{ij}]$ be the deprivation matrix whose typical element g_{ij} is defined by $g_{ij}=w_j$ when $y_{ij} < z_j$ and $g_{ij}=0$ when $y_{ij} \geq z_j$. In the case of the MEPI, the element of the achievement matrix being strictly non-numeric in nature, the cut-off is defined as a set of conditions to be met (see also Table 2). The entry ij of the matrix is equivalent to the variable weight w_j when a person i is deprived in variable j, and zero when the person is not deprived. Following this, we construct a column vector c of deprivation counts, where the ith entry $c_i = \sum_{j=1}^{d} g_{ij}$ represents the sum of weighted deprivations suffered by person i. It must be noted here that the technique whereby the weights are summed up, as opposed to a weighted score, is not novel in that it has been applied in a number of multi-criteria methodologies.[1]

We then identify the persons multidimensionally energy poor by defining a cut-off $k > 0$ and applying it across the column vector, and consider a person as energy poor if her weighted deprivation count c_i exceed k. Therefore, $c_i(k)$ is set to zero when $c_i \leq k$ and equals c_i when $c_i > k$. Thus, $c(k)$ represents the censored vector of deprivation counts, and it is different to c in that it counts zero deprivation for those not identified as multidimensionally energy poor.

Finally, we compute the headcount ratio H, which represents the proportion of people that are considered energy poor.[2] With q as the number of energy poor people (where $c_i > k$) and n the total, we have $H=q/n$, which represents the incidence of multidimensional energy poverty. The average of the censored weighted deprivation counts $c_i(k)$ represents the intensity of multidimensional energy poverty A. More formally, we calculate $A = \sum_{i=1}^{n} c_i(k)/q$. The MEPI captures information on both the incidence and the intensity of energy poverty, and is defined as MEPI $= H \times A$.

For the uncertainty analysis, we use a Monte Carlo method and compute the MEPI recurrently ($n=1000$) based on the normally distributed random weights. The results are in turn non-deterministic and are in the form of probability density functions due to the stochastic weights. Based on this, we derive the respective uncertainty bands that we arbitrarily define as the range between the 5th and 95th percentile.

The MEPI methodology provides a number of advantages. Notably, it focuses on the energy services and is based on data related to energy deprivations, as opposed to deriving information indirectly through variables that are presumed to be correlated (e.g. energy or electricity consumption). Additionally, it captures both the incidence (number of energy poor people) as well as the intensity (how energy poor they are). Related to this, the OPHI methodology, applied here to energy poverty, respects the condition of dimensional (or variable) monotonicity. That is, both if an additional person becomes poor and if a person already considered as multidimensionally poor becomes poor in additional variable(s), it is reflected by an increase in the aggregated value. Another virtue of the methodology is its decomposability. Because the data used as input are at micro-level (households or individuals), the tool allows

[1] E.g. ELECTRE (ELimination Et Choix Traduisant la REalité).

[2] For the sake of the simplicity of the argument, we refer in the first section of the description of the methodology to the individual as a unit. The data used stem from household surveys, the first steps of the calculation are made at household level, under the assumption that energy poverty can be characterized at such level. When computing the headcount and the average censored weighted deprivation, we include the number of persons per household (data available from the surveys), as well as the sampling weight to ensure representativeness.

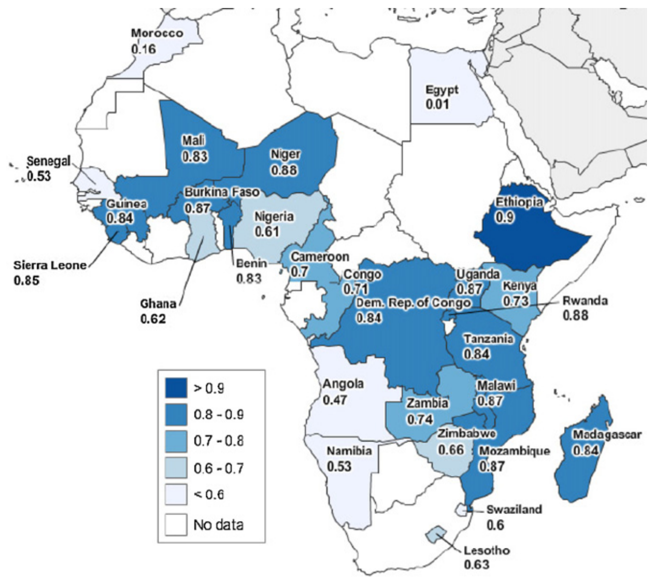


Fig. 1. MEPI for selected African countries. Visual created with van Cappelle [40].

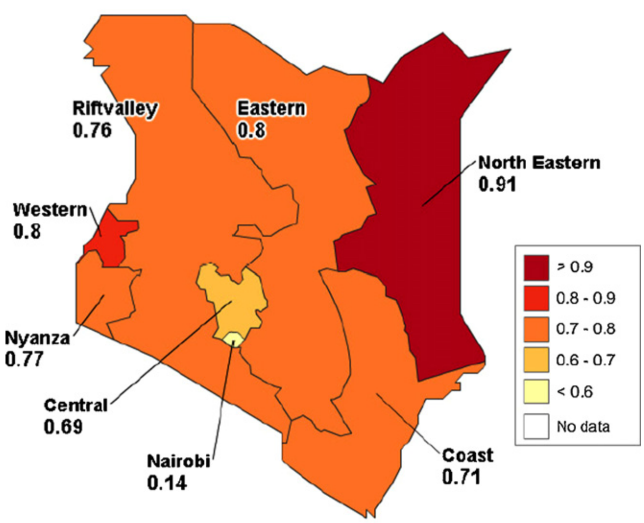


Fig. 2. MEPI at sub-national level (Kenya).

for a wide range of analyses focusing on sub-groups (e.g. wealth classes).

4. Results

We calculated the MEPI to all the African countries for which appropriate data are available,[3] setting the multidimensional energy poverty cut-off k to 0.3. It implies that a person is considered as energy poor if, for instance, she has no access to clean cooking or does not benefit from energy services supplied by electricity.

Fig. 1 shows the results for the MEPI in Africa. The countries are classified according to the degree of energy poverty, ranging from acute energy poverty (MEPI > 0.9; e.g. Ethiopia) to moderate energy poverty (MEPI < 0.6; Angola, Egypt, Morocco, Namibia, Senegal). The details on the results for the headcount ratio, intensity of poverty and MEPI are available in Annex A. As complementary information, we also report on individual indicators, such as the

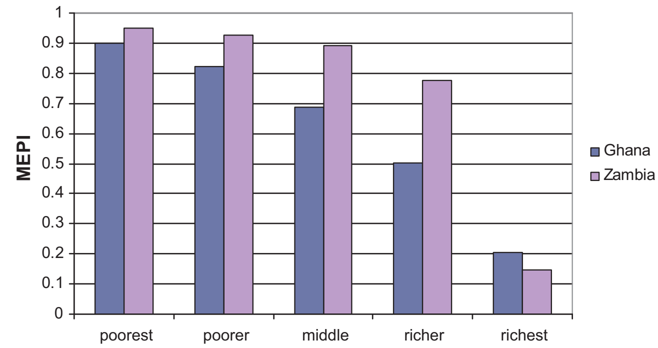


Fig. 3. MEPI by wealth index quintile in Ghana and Zambia.

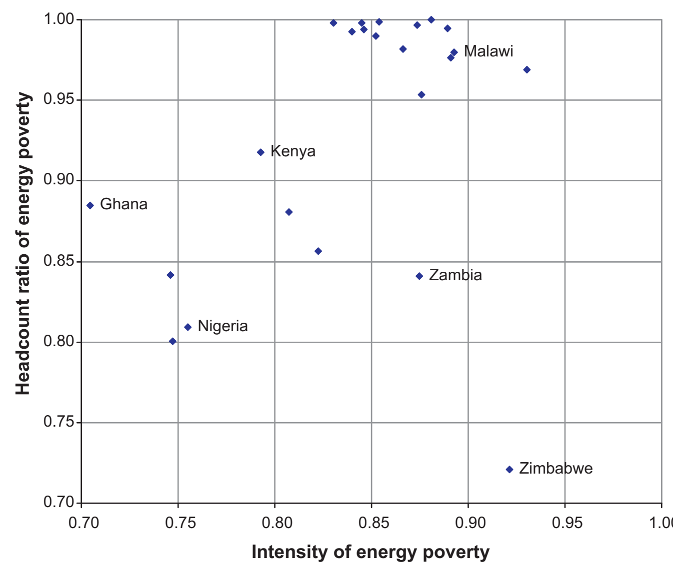


Fig. 4. Headcount ratio vs. intensity of energy poverty for sub-Saharan countries.

electrification rate and the rate of use of modern[4] cooking fuels, in the same annex.

National statistics often mask significant sub-national disparities. To test this, we compute the MEPI at the district level in Kenya, as an illustration. Fig. 2 shows a stark contrast with regard to the level of energy poverty between the capital, where the MEPI is similar to that of the country of Morocco, and the Western and North Eastern districts which suffer from severe energy poverty.

We next turn to decomposing the energy poverty metric based on wealth categories. Showcasing two examples, Fig. 3 indicates that the energy poverty stratification varies notably between countries. While the MEPI in the two most economically deprived and well-off quintiles in Ghana and Zambia is comparable, it is notably different for the middle classes. In Zambia, there is a steep decline in energy poverty when moving from the richer to the richest quintile, whereas the reduction in energy poverty appears to be more evenly distributed in the case of Ghana.

In Fig. 4, we plot the headcount ratio, i.e. the ratio of people considered as energy poor, against the intensity of poverty which indicates how poor the energy poor are. It is useful to consider the outliers on the graph. It indicates that for the countries below an imaginary trend line, the intensity of energy poverty is significantly higher compared to the headcount ratio of energy poor. The opposite holds for those countries above the line. In other words,

[3] That is, data for the indicators of the MEPI are available in the DHS dataset from survey phase IV and/or V.

[4] i.e. non solid.

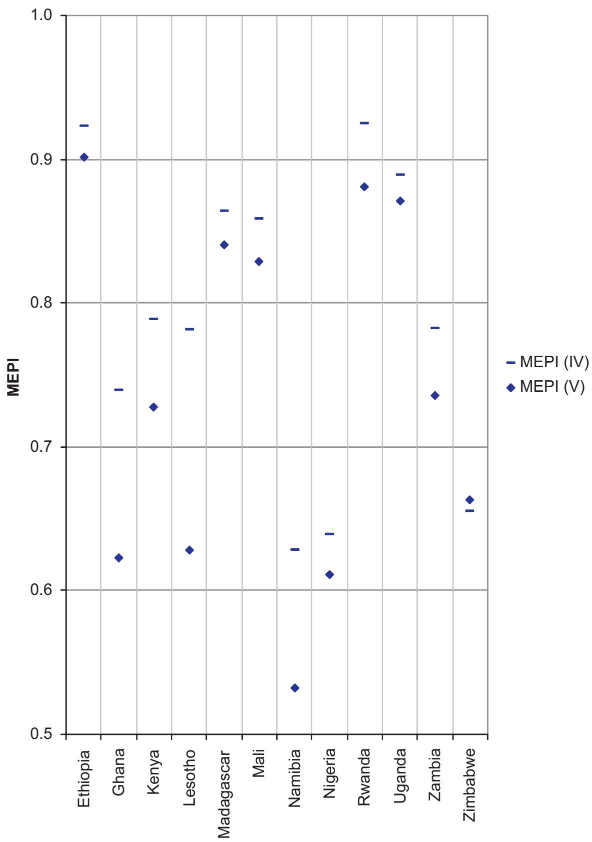


Fig. 5. Evolution over time of the MEPI (based on comparison between data from DHS surveys of phases IV and V) for sub-Saharan countries.

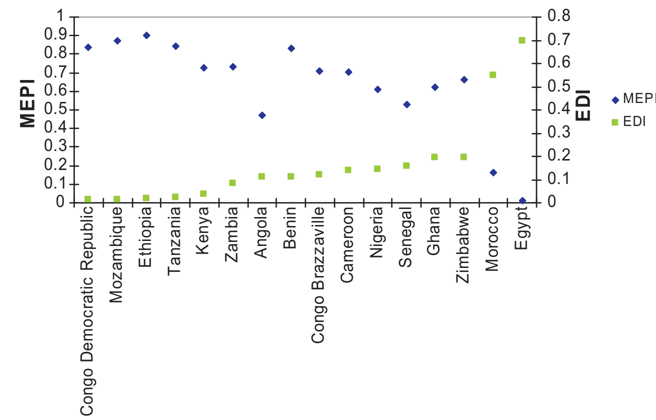
although the MEPI value of Ghana and Nigeria is comparable, the ratio of people experiencing energy poverty is higher in Ghana. In contrast, the intensity of energy poverty is greater in Nigeria. Similarly, the intensity of energy poverty is almost identical between Malawi and Zambia. Nonetheless, there are more energy poor, in relative terms, in the former than in the latter.

For a few countries, data are available from DHS surveys of phases IV and V.[5] Based on this, it is possible to explore, to a small degree, the evolution of the MEPI over time. Fig. 5 shows the results of the MEPI computed based on both survey datasets. Although the finding is not robust enough to allow generalization, the graph seems to indicate that progress in reducing energy poverty happens more rapidly as energy poverty declines.[6] For instance, the difference in the MEPI between the two data sets is greater for Ghana and Namibia than for the other countries. Another observation is that one can note a reduction in energy poverty in all countries but Zimbabwe.

4.1. Comparison with other indices

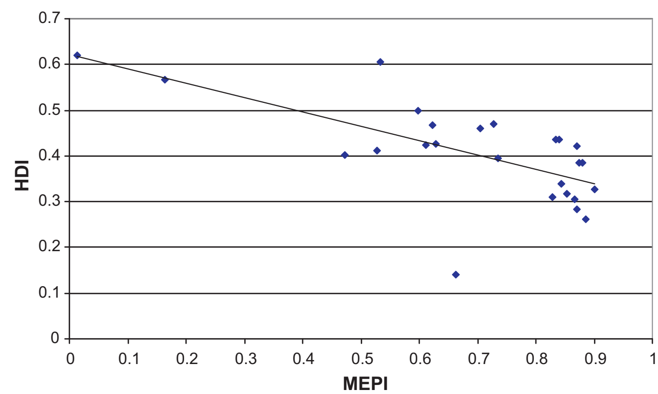
Next, we compare the new metric we created with the landmark Energy Development Index (EDI) from the IEA (see, e.g. [9]). It must be underlined here that the EDI and the MEPI, while both designed to provide information with regard to access to modern energy services, focus on different aspects of energy for development. The EDI is a measure of energy system transition towards modern fuels whereas the MEPI evaluates energy poverty. With this in mind, Fig. 6 shows the comparison between the MEPI and EDI for all African countries for which data are available for both metrics. As expected, the two indices are negatively correlated. That is, the EDI shows a lower level of energy system development for those countries for which the MEPI has identified acute energy poverty. The MEPI and the EDI are complementary measures which characterize different aspects of the energy – development nexus.

Finally, we also compare the outcomes of the MEPI with the HDI,[7] arguably the reference index for human development, to gain insight on the hypothesis of the strong link between energy and development. Fig. 7 shows a negative correlation between the two indices ($b = -.31$, $p < 0.000$, $R^2 = 0.43$).



Data source for EDI: IEA (2010).

Fig. 6. Comparison between MEPI and EDI for selected African countries. Data source for EDI: IEA [9].



Data source for HDI: UNDP (2010).

Fig. 7. Comparison between MEPI and HDI for selected African countries. Data source for HDI: UNDP [22].

5. Discussion

We appreciate the need for pragmatism in the development of an index that is easily computable, flexible enough to be used in various contexts, and that acknowledges the issues related to the lack of availability of reliable, comprehensive datasets. It must be reiterated that composite indices, by their very nature, are incapable of reflecting the full extent of the complexity of the issue they measure. Regardless of the specifics of the model, a composite index will

[5] DHS surveys phases IV and V span 1997–2003 and 2003–present, respectively.

[6] To test this, we carry out a correlation analysis between the MEPI score of the phase IV and the difference in the MEPI score between both phases shows to find a negative correlation, as expected. The tendency (not statistically relevant at 95%) is therefore for the difference in the MEPI over time to be greater when the energy poverty level is lower initially; ($b = -.48$, $p < 0.51$, $R^2 = 0.04$).

[7] Edition 2010.

always involve some form of reduction of the variety of information included in the various indicators individually. Also, we do not dispute the value of analysing the indicators independently, but argue that it is additionally useful to construct an aggregated measure. Indeed, it can provide a crucial input into an overall comparison between communities.

The issue of weights has generated much debate in the literature. Every aggregated multidimensional measure places some weights on the various factors, either explicitly or implicitly. In this paper, we have defined the weights based on ‘expert opinion’ for the purpose of demonstrating the methodology. We recognise the arbitrary nature of those, as well as the fact that the weighting structure might have to be adjusted depending on the objective of the analysis and context.

The quality of a composite index, apart from the issues related to the aggregation model, is intrinsically linked to the quality of its components and thus the quality and reliability of the underlying variables. This represents a critical issue in the case of energy poverty, since it systemically lacks an information base that is of quality, reliability, and comprehensive, despite current and most welcome efforts to improve it. The data used for this analysis represent imperfect proxies drawn from surveys, which have their own limitations, not specifically developed for energy purposes.

The following section summarises the outcome of a series of sensitivity analyses intended to test the robustness of the methodology and the results.

5.1. Sensitivity analysis

Beside the data issue, there is also uncertainty inherent to the methodology and assumptions. Indeed, the choice of the indicators, constrained by the availability of data, as well as the structure of the aggregating model influence the outcome of the analysis. With this in mind, we present a series of tests by modifying some of the key parameters.

- We vary the cut-off of multidimensional poverty, k, and evaluate the impact on the MEPI. To this purpose, we classify the countries in deciles based on the MEPI and consider the change in classification when the cut-off is altered (between 0.2 and 0.4) to assess the robustness of the analysis (see results in Annex B). The change in the energy poverty cut-off does not lead to significant changes in the country classification. In fact, only two countries (Lesotho and Swaziland) change decile in this analysis. Annex C shows the change in the MEPI in absolute terms.
- We test the stability of the country rankings to changes in the multidimensional poverty cut-off by applying two different methodologies, namely the Spearman’s and Kendall’s rank correlation coefficient.[8] The results (see Annex D) show a very high correlation between the rankings, ranging from 0.9956 to 1 for the Spearman test and from 0.9735 to 1 for that of Kendall, implying that the change in the cut-off only marginally affects the results.
- In addition to this, and as described in Section 3.4, we compute the algorithm of the MEPI with the weights as logistic functions as a means of capturing some of the uncertainty associated with determining those. The output is a probability density function. Fig. 8 summarises the results by showing the MEPI score together with the respective uncertainty band that we arbitrarily define as the range between the 5th and 95th percentile of the probability density function. The graph provides a sense of the effect of slightly varying the weighting structure. It is important to note that the generated pseudo-confidence intervals are to be interpreted with care. They are useful to account for some of the uncertainty about the weights, and provide indications related to the robustness of cross-country comparisons.[9]

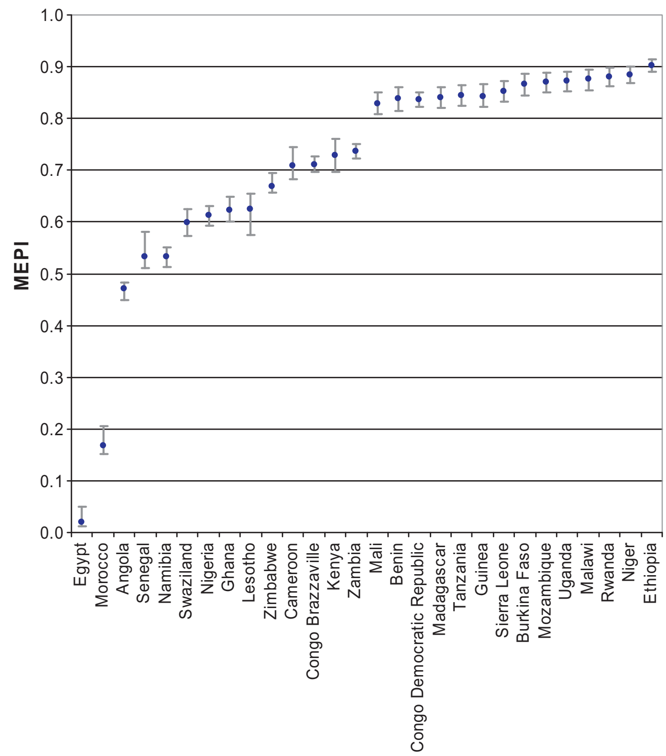


Fig. 8. MEPI including the pseudoconfidence interval due to the uncertainty in the weighting of the indicators.

The effect is different amongst the countries. The outcome of the stochastic computation of the MEPI is presented graphically for selected countries in Annex E. The graphs show that, in some cases, the dispersion is relatively small (e.g. Zambia: $\sigma = 0.0087$) whereas it can be notably greater for others (e.g. Kenya: $\sigma = 0.0197$).

Also, the probability density functions resulting from the stochastic computing of the MEPI are close to being normally distributed in most cases. As illustrative examples, the skewness is 0.031 and −0.028 for Zambia and Kenya, respectively. However, the skewness is more pronounced for a few countries, such as Angola (−1.240). See also Annex E for a graphical representation. The non-normal distribution of the results calls for caution in applying the methodology with deterministic parameters. Indeed, in those cases, the score is relatively sensitive to the choice of weights and multidimensional cut-off.

5.2. Further work

We have outlined and tested a new tool to measure energy poverty at various levels. There are a number of possible refinements in terms of both the methodology itself and its application and further testing.

The indicators picked for this analysis, as well as the various parameters chosen, are for the purpose of illustrating the

8 The Spearman’s rank correlation coefficient is based on the changes in country ranks between a pair of rankings, whereas the Kendall’s coefficient is calculated by comparing each pair of countries in a pair of rankings.

9 For instance, they allow for probing statements like: ‘With the most favourable weights, country A does not fare better than country B with the least favourable weights’.

application of the methodology. The results, as insightful as they might be, must be interpreted bearing in mind that they depend on the underlying model. Further work could include applying the methodology in various contexts. For instance, there is scope for refining the methodology to assess very high levels of energy poverty in more detail. The analysis of those cases would most likely benefit from a specific set of indicators and weights, as well as possibly another source of data.

An intermediate step would be to decompose the current analysis and assess the composition of energy poverty in detail to gather insights from the differences between countries. Indeed, valuable policy insights could be derived from a better understanding of what constitutes energy poverty in different contexts. For instance, in Benin, some households benefit from electricity but access to modern cooking is predominantly low. In contrast and with a similar energy poverty headcount ratio, Ethiopian households are better off in comparison with regard to cooking, but the electrification rate is notably lower.

Another area of further work is the extension of the application of the methodology to other regions and countries, including those for which the datasets are patchy. Beside this, a periodical updating of the analysis would be most useful. It might be appropriate, though, to consider changes in the set of indicators, weights and cut-offs, as data improve.

6. Conclusion

Providing a rigorous analytical basis for policy-making by developing and applying a robust set of metrics for measuring energy poverty is central to the implementation of any global, regional or national target. Designing the measurement toolbox and implementing a reporting system can help move energy access to the heart of the development agenda. The methodology outlined and tested in this paper contributes to efforts geared towards providing evidence-based information to inform the design and implementation of measures and policies to address the issue of energy poverty.

We develop and apply a tool to evaluate energy poverty at various levels – the Multidimensional Energy Poverty Index (MEPI). The MEPI, while constrained by the data paucity characterizing this field of work, is innovative on a number of grounds. The methodology is based on the concept of multidimensional poverty and is inspired by the relevant literature. The index is composed of two components: a measure of the incidence of energy poverty, and a quantification of its intensity. The methodology focuses on the deprivation in terms of energy, and places energy services at the core of the analysis. Also, as the quantification is based on detailed and extensive micro-data stemming from household surveys, a great deal of decomposition analysis is possible which provides a wealth of policy relevant information. Nevertheless, the MEPI will only form one instrument in monitoring progress and designing and implementing good policy in the area of energy poverty.

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Annex A. Detailed results for African countries: headcount ratio and intensity of energy poverty, and the composite MEPI, as well as individual indicators, alongside other related indices

Country (year of most recent DHS survey)	Headcount ratio	Intensity of energy poverty	MEPI	Electrification (%)	Modern cooking fuel (%)	EDI	HDI
Angola (2006–2007)	0.59	0.79	0.47	41.6	52.5	0.111	0.403
Benin (2006)	0.99	0.84	0.83	22.2	0.7	0.111	0.435
Burkina Faso (2003)	0.98	0.87	0.87	10.4	2.0		0.305
Cameroon (2004)	0.86	0.82	0.70	46.2	16.0	0.138	0.46
Congo Brazzaville (2009)	0.88	0.81	0.71	34.7	15.0	0.122	
Congo Democratic Republic (2007)	0.95	0.88	0.84	17.6	4.6	0.012	
Egypt (2008)	0.03	0.48	0.01	99.4	99.5		0.62
Ethiopia (2005)	0.97	0.93	0.90	12.2	3.4	0.019	0.328
Ghana (2008)	0.88	0.70	0.62	56.1	11.7	0.195	0.467
Guinea (2005)	1.00	0.85	0.84	20.9	0.2		0.34
Kenya (2008–2009)	0.92	0.79	0.73	18.2	9.7	0.038	0.47
Lesotho (2009)	0.84	0.75	0.63	15.7	33.9		0.427
Liberia (2007)			[a]	3.3			0.3
Madagascar (2008–2009)	0.99	0.85	0.84	16.5	0.6		0.435
Malawi (2004)	0.98	0.89	0.87	7.5	2.0		0.385
Mali (2006)	1.00	0.83	0.83	17.5	0.3		0.309
Morocco (2003–2004)	0.29	0.57	0.16	76.7	89.9		0.567
Mozambique (2003)	0.98	0.89	0.87	11.0	2.8	0.015	0.284
Namibia (2006–2007)	0.67	0.79	0.53	39.3	35.4		0.606
Niger (2006)	0.99	0.89	0.88	10.5	0.6		0.261
Nigeria (2008)	0.81	0.75	0.61	47.9	20.9	0.144	0.423
Rwanda (2007–2008)	1.00	0.88	0.88	6.7	0.0		0.385
Senegal (2005)	0.66	0.80	0.53	46.5	38.9	0.157	0.411
Sierra Leone (2008)	1.00	0.85	0.85	11.1	0.1		0.317
Swaziland (2006–2007)	0.80	0.75	0.60	29.9	24.0		0.498
Tanzania (2007–2008)	0.99	0.85	0.84	10.9	1.5	0.025	
Uganda (2006)	1.00	0.87	0.87	7.7	0.5		0.422
Zambia (2007)	0.84	0.87	0.74	21.0	16.0	0.083	0.395
Zimbabwe (2005–2006)	0.72	0.92	0.66	34.0	29.9	0.197	0.14

Note: Own calculation based on data from [41]; EDI: [3]; HDI: [22].

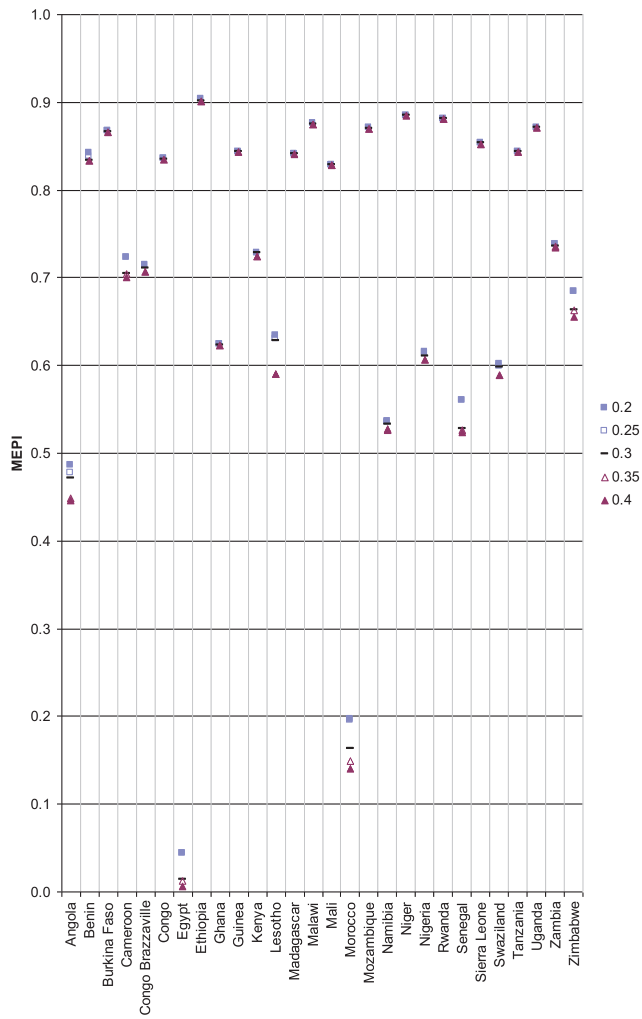
[a] Not available; missing data.

Annex B. Effects of multidimensional energy deprivation cut-off change on distribution of countries in deciles

MEPI deciles	0.2	0.25	0.3	0.35	0.4
1 (highest)	Ethiopia	Ethiopia	Ethiopia	Ethiopia	Ethiopia
2	Benin Burkina Faso Congo Democratic Republic Guinea Madagascar Malawi Mali Mozambique Niger Rwanda Sierra Leone Tanzania Uganda	Benin Burkina Faso Congo Democratic Republic Guinea Madagascar Malawi Mali Mozambique Niger Rwanda Sierra Leone Tanzania Uganda	Benin Burkina Faso Congo Democratic Republic Guinea Madagascar Malawi Mali Mozambique Niger Rwanda Sierra Leone Tanzania Uganda	Benin Burkina Faso Congo Democratic Republic Guinea Madagascar Malawi Mali Mozambique Niger Rwanda Sierra Leone Tanzania Uganda	Benin Burkina Faso Congo Democratic Republic Guinea Madagascar Malawi Mali Mozambique Niger Rwanda Sierra Leone Tanzania Uganda
3	Cameroon Congo Brazzaville Kenya Zambia	Cameroon Congo Brazzaville Kenya Zambia	Cameroon Congo Brazzaville Kenya Zambia	Cameroon Congo Brazzaville Kenya Zambia	Cameroon Congo Brazzaville Kenya Zambia
4	Ghana Lesotho Nigeria Zimbabwe **Swaziland**	Ghana Lesotho Nigeria Zimbabwe	Ghana Lesotho Nigeria Zimbabwe	Ghana Nigeria Zimbabwe	Ghana Nigeria Zimbabwe
5	Namibia Senegal	Namibia Senegal Swaziland	Namibia Senegal Swaziland	**Lesotho** Namibia Senegal Swaziland	**Lesotho** Namibia Senegal Swaziland
6	Angola	Angola	Angola	Angola	Angola
7					
8					
9	Morocco	Morocco	Morocco	Morocco	Morocco
10 (lowest)	Egypt	Egypt	Egypt	Egypt	Egypt

Bold indicates countries that change decile in this sensitivity analysis.

Annex C. Effects of multidimensional energy deprivation cut-off change on the MEPI



Annex D. Correlation in the countries ranking when the multidimensional energy deprivation cut-off is changed

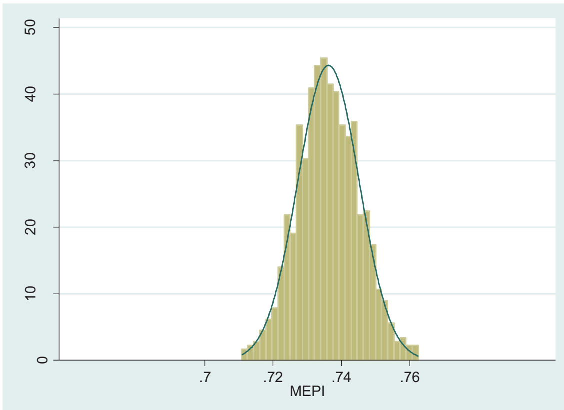
Spearman	0.2	0.25	0.3	0.35	0.4
0.2	1				
0.25	0.9995*	1			
0.3	0.9973*	0.9984*	1		
0.35	0.9956*	0.9967*	0.9984*	1	
0.4	0.9956*	0.9967*	0.9984*	1.0000*	1

Kendall	0.2	0.25	0.3	0.35	0.4
0.2	1				
0.25	0.9947*	1			
0.3	0.9788*	0.9841*	1		
0.35	0.9783*	0.9735*	0.9894*	1	
0.4	0.9783*	0.9735*	0.9894*	1.0000*	1

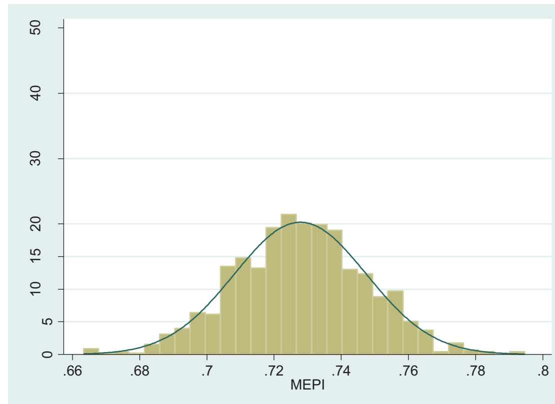
Note: $n = 28$.

* Statistically significant at 99%.

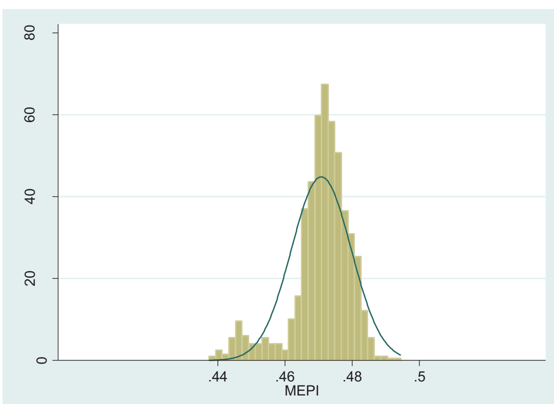
Annex E. Selected illustrative detailed MEPI results as probability density functions with fitted normally distributed function



Zambia



Kenya



Angola

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